Analysis of spatial effects in vine and olive crops across Portuguese regions

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Analysis of Spatial Effects in Vine and Olive Crops across Portuguese Regions

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Abstract

The consideration of spatial effects at a regional level is becoming increasingly frequent and the work of Anselin (1988), among others, has contributed to this. This study analyses, through cross-section estimation methods, the influence of spatial effects in the NUTs III vine and olive crops of mainland Portugal, in 1999 (the last data available), considering the Verdoorn relationship as a base of study. To analyse the data, by using Moran I statistics, and estimation results, considering the spatial lag and spatial error component, it is stated that there are positive spatial autocorrelation (variables of each of the regions develop in a similar manner to each of the neighbouring regions), above all in vine.

Keywords: spatial econometrics; vine and olive crops; Portuguese regions

1. Introduction

The influence of neighbouring locations (parishes, councils, districts, regions, etc) in the development of a particular area, through the effects of spatial spillovers, is increasingly considered in more recent empirical studies; a fact which has been highlighted by Anselin (2002a). Anselin (1988 and 2001) and Anselin and Bera (1998), who refer to the inclusion of spatial effects as being important from an econometric point of view. If the underlying data arises from processes which include a spatial dimension, and this is omitted, the estimations may lead to inconsistent estimations.

Following on from these studies, the development of productivity of a particular region, for example, can be influenced by the development of productivity in neighbouring regions, through external spatial factors. The existence or non-existence of these effects can be determined through a number of techniques which have been developed for spatial econometrics, where Anselin, among others, in a number of studies has made a large contribution. Paelinck (2000) has brought a number of theoretical contributions to the aggregation of models in spatial econometrics, specifically concerning the structure of parameters. Anselin (2002b) considered a group of specification tests based on the method of Maximum Likelihood to test the alternative proposed by Kelejian and Robinson (1995), related to perfecting the spatial error component. Anselin (2002c) has presented a classification of specification for models of spatial econometrics which incorporates external spatial factors. Anselin (2002d) has reconsidered a number of conceptual matters related to implementing an explicit spatial perspective in applied econometrics. Baltagi et al. (2003) has sought to present improvements in specification tests (testing whether the more correct specification of models is with the spatial lag component or the spatial error component) LM (Lagrange Multiplier), so as to make it more adaptable to spatial econometrics. Anselin et al. (1996) has proposed a simple, robust diagnostic test, based on the OLS method, for the spatial autocorrelation of errors in the presence of spatially redundant dependent variables and vice-versa, applying the modified LM test developed by Bera and Yoon (1993).

This study seeks to analyse the spatial effects for vine and olive crops of regions (NUTs III) of mainland Portugal, in 1999, through techniques of cross-section spatial econometrics. To do so, the rest of the study is structured as follows: in the second part some studies which have already been developed in the area of spatial econometrics, specifically concerning Verdoorn's Law, are presented; in the third part some theoretical considerations of spatial econometrics are presented; in the fourth, the models considered are explained; in the fifth the data is analysed based on techniques of spatial econometrics developed to explore spatial data; the sixth presents estimations, taking into account spatial effects; and in the seventh part the main conclusions obtained through this study are presented.

2. Empirical contributions based on spatial effects

There have been various studies carried out concerning Verdoorn's Law considering the possibility of there being spatial spillover effects.

Concerning Verdoorn's Law and the effects of spatial lag and spatial error, Bernat (1996), for example, tested Kaldor's three laws of growth[1] in North American regions from 1977-1990. The results obtained by Bernat clearly supported the first two of Kaldor's laws and only marginally the third. Fingleton and McCombie (1998) analysed the importance of scaled growth income, through Verdoorn's Law, with spatial lag effects in 178 regions of the European Union in the period of 1979 to 1989 and concluded that there was a strong scaled growth income. Fingleton (1999), with the purpose of presenting an alternative model between Traditional and New Geographical Economics, also constructed a model with the equation associated to Verdoorn's Law, augmented by endogenous technological progress involving diffusion by spillover effects and the effects of human capital. Fingleton applied this model (Verdoorn) to 178 regions of the European Union and concluded there was significant scaled growth income with interesting results for the coefficients of augmented variables (variable dependent on redundancy, rurality, urbanisation and diffusion of technological innovations)) in Verdoorn's equation.

Few studies have been carried out on analysing the conditional productivity convergence with spatial effects and none, at least to our knowledge, concerning productivity being dispersed by the various economic sectors. Fingleton (2001), for example, has found a spatial correlation in productivity when, using the data from 178

[1] Kaldor's laws refer to the following: i) there is a strong link between the rate of growth of national product and the rate of growth of industrial product, in such a way that industry is the motor of economic growth; ii) The growth of productivity in industry and endogeny is dependent on the growth of output (Verdoorn's law); iii) There is a strong link between the growth of non-industrial product and the growth of industrial product, so that the growth of output produces externalities and induces the growth of productivity in other economic sectors..

regions of the European Union, he introduced spillover effects in a model of endogenous growth. Abreu et al. (2004) have investigated the spatial distribution of growth rates in total factor productivity, using exploratory analyses of spatial data and other techniques of spatial econometrics. The sample consists of 73 countries and covers the period 1960-200. They found a significant spatial autocorrelation in the rates of total factor productivity, indicating that high and low values tend to concentrate in space, forming the so-called clusters. They also found strong indicators of positive spatial autocorrelation in total factor productivity, which increased throughout the period of 1960 to 2000. This result could indicate a tendency to cluster over time.

On the other hand, there is some variation in studies analysing conditional convergence of product with spatial effects. Armstrong (1995) defended that the fundamental element of the convergence hypothesis among European countries, referred to by Barro and Sala-i-Martin, was the omission of spatial autocorrelation in the analysis carried out and the bias due to the selection of European regions. Following on from this, Sandberg (2004), for example, has examined the absolute and conditional convergence hypothesis across Chinese provinces from the period 1985 to 2000 and found indications that there had been absolute convergence in the periods 1985-1990 and 1985-2000. He also found that there had been conditional convergence in the sub-period of 1990-1995, with signs of spatial dependency across adjacent provinces. Arbia et al. (2004) have studied the convergence of gross domestic product per capita among 125 regions of 10 European countries from 1985 to 1995, considering the influence of spatial effects. They concluded that the consideration of spatial dependency considerably improved the rates of convergence. Lundberg (2004) has tested the hypothesis of conditional convergence with spatial effects between 1981 and 1990 and, in contrast to previous results, found no clear evidence favouring the hypothesis of conditional convergence. On the contrary, the results foresaw conditional divergence across municipalities located in the region of Stockholm throughout the period and for municipalities outside of the Stockholm region during the 1990s.

Spatial econometric techniques have also been applied to other areas besides those previously focused on. Longhi et al. (2004), for example, have analysed the role of spatial effects in estimating the function of salaries in 327 regions of Western Germany during the period of 1990-1997. The results confirm the presence of the function of salaries, where spatial effects have a significant influence. Anselin et al. (2001) have analysed the economic importance of the use of analyses with spatial regressions in agriculture in Argentina. Kim et al. (2001) have measured the effect of the quality of air on the economy, through spatial effects, using the metropolitan area of Seoul as a case study. Messner et al. (2002) have shown how the application of recently developed techniques for spatial analysis, contributes to understanding murder amongst prisoners in the USA.

3. Theoretical considerations of spatial econometrics, based on the Verdoorn relationship

In 1949 Verdoorn detected that there was an important positive relationship between the growth of productivity of work and the growth of output. He defended that causality goes from output to productivity, with an elasticity of approximately 0.45 on average (in cross-section analyses), thus assuming that the productivity of work is endogenous.

Kaldor (1966 and 1967) redefined this Law and its intention of explaining the causes of the poor growth rate in the United Kingdom, contesting that there was a strong positive relationship between the growth of work productivity (p) and output (q), so that, p=f(q). Or alternatively, between the growth of employment € and the growth of output, so that, e=f(q). This is because, Kaldor, in spite of estimating Verdoorn's original relationship between the growth of productivity and the growth of industrial output (for countries of the OECD), gave preference to the relationship between the growth of work and the growth of output, to prevent spurious effects (double counting, since p=q-e). This author defends that there is a significant statistical relationship between the growth rate of employment or work productivity and the growth rate of output, with a regression coefficient belied to be between 0 and 1 ($0 \leq b \leq 1$), which could be sufficient condition for the presence of dynamic, statistically growing scale economies. The relationship between the growth of productivity of work and the growth of output is stronger in industry, given that mostly commercialised products are produced. This relationship is expected to be weaker for other sectors of the economy (services and agriculture), since services mostly produce non-transactional products (the demand for exports is the principal determining factor of economic growth, as was previously mentioned). And agriculture displays decreasing scale incomes, since it is characterised by restrictions both in terms of demand (inelastic demand) and supply (unadjusted and unpredictable supply).

More recently, Bernat (1996), when testing Kaldor's three laws of growth in regions of the USA from the period of 1977 to 1990, distinguished two forms of spatial autocorrelation: spatial lag and spatial error. Spatial lag is represented as follows: $y = \rho W y + X\beta + \varepsilon$, where y is the vector of endogenous variable observations, , W is the distance matrix, X is the matrix of endogenous variable observations, β is the vector of coefficients, ρ is the self-regressive spatial coefficient and ε is the vector of errors. The coefficient ρ is a measurement which explains how neighbouring observations affect the dependent variable. The spatial error model is expressed in the following way: $y = X\beta + \mu$, where spatial dependency is considered in the error term $\mu = \lambda W \mu + \xi$.

To resolve problems of spatial autocorrelation, Fingleton and McCombie (1998) considered a spatial variable which would capture the spillovers across regions, or, in other words, which would determine the effects on productivity in a determined region i, on productivity in other surrounding regions j, as the distance between i and j. The model considered was as follows:

$p = b_0 + b_1 q + b_2 slp + u$, Verdoorn's equation with spatially redundant productivity (1)

where the variable p is productivity growth, q is the growth of output, $slp = \sum_j W_{ij} p_j$ (spatially redundant productivity variable), $W_{ij} = W_{ij}^* / \sum_j W_{ij}^*$ (matrix of distances), $W_{ij}^* = 1/d_{ij}^2$ (se $d_{ij} \leq 250Km$), $W_{ij}^* = 0$ (se $d_{ij} > 250Km$), d_{ij} is the distance between regions i and j and u is the error term.

Fingleton (1999), has developed an alternative model, whose final specification is as follows:

$p = \rho p_0 + b_0 + b_1 R + b_2 U + b_3 G + b_4 q + \xi$, Verdoorn's equation by Fingleton (2) where p is the growth of inter-regional productivity, p_0 is the growth of extra-regional productivity (with the significance equal to the slp variable of the previous model), R represents rurality, U represents the level of urbanisation and G represents the diffusion of new technologies. The levels of rurality and urbanisation, symbolised by the R and U variables, are intended to indirectly represent the stock of human capital.

A potential source of errors of specification in spatial econometric models comes from spatial heterogeneity (Lundberg, 2004). There are typically two aspects related to spatial heterogeneity, structural instability and heteroskedasticity. Structural instability has to do with the fact that estimated parameters are not consistent across regions. Heteroskedasticity has to do with errors of specification which lead to non-constant variances in the error term. To prevent these types of errors of specification and to test for the existence of spatial lag and spatial error components in models, the results are generally complemented with specification tests. One of the tests is the Jarque-Bera test which tests the stability of parameters. The Breuch-Pagan and Koenker-Bassett, in turn, tests for heteroskedasticity. The second test is the most suitable when normality is rejected by the Jarque-Bera test. To find out if there are spatial lag and spatial error components in the models, two robust Lagrange Multiplier tests are used (LM_E for "spatial error" and LM_L for "spatial lag"). In brief, the LM_E tests the null hypothesis of spatial non-correlation against the alternative of the spatial error model ("lag") and LM_L tests the null hypothesis of spatial non-correlation against the alternative of the spatial lag model to be the correct specification.

According to the recommendations of Florax et al. (2003) and using the so-called strategy of classic specification, the procedure for estimating spatial effects should be carried out in six steps: 1) Estimate the initial model using the procedures using OLS; 2) Test the hypothesis of spatial non-dependency due to the omission spatially redundant variables or spatially autoregressive errors, using the robust tests LM_E and LM_L; 3) If none of these tests has statistical significance, opt for the estimated OLS model, otherwise proceed to the next step, 4) If both tests are significant, opt for spatial lag or spatial error specifications, whose test has greater significance, otherwise go to step 5;; 5) If LM_L is significant while LM_E is not, use the spatial lag specification; 6) If LM_E is significant while LM_L is not, use the spatial error specification.

A test usually used to indicate the possibility of global spatial autocorrelation is the Moran's I test[2].

Moran's I statistics is defined as:

$$I = \frac{n}{S} \frac{\sum_i \sum_j w_{ij}(x_i - u)(x_j - u)}{\sum_i (x_i - u)^2} \text{, Moran's global autocorrelation test} \quad (3)$$

where n is the number of observations and x_i and x_j are the observed rates of growth in the locations i and j (with the average u). S is the constant scale given by the sum of all the distances: $S = \sum_i \sum_j w_{ij}$.

When the normalisation of weighting on the lines of the matrix for distances is carried out, which is preferable (Anselin, 1995), S equals n, since the weighting of each line added up should be equal to the unit, and the statistical test is compared with its theoretical average, I=-1/(n-1). Then $I \to 0$, when $n \to \infty$. The null hypothesis H_0: I=-1/(n-1) is tested against the alternative hypothesis H_A: I≠-1/(n-1). When H_0 is rejected and I>-1/(n-1) the existence of positive spatial autocorrelation can be verified. That is to say, the high levels and low levels are more spatially concentrated (clustered) than would be expected purely by chance. If H_0 is rejected once again, but I<-1/(n-1) this indicates negative spatial autocorrelation.

Moran's I local autocorrelation test investigates if the values coming from the global autocorrelation test are significant or not:

$$I_i = \frac{x_i}{\sum_i x_i^2} \sum_j w_{ij} x_j \text{, Moran's local autocorrelation test} \quad (4)$$

where the variables signify the same as already referred to by Moran's I global autocorrelation test.

4. Verdoorn's model with spatial effects

Bearing in mind the previous theoretical considerations, what is presented next

[2] A similar, but less well-known test is Geary's C test (Sandberg, 2004).

is the model base used to analyse Verdoorn's law with spatial effects, at a regional and agricultural sector level in mainland Portugal.

As a result, to analyse Verdoorn's Law in the agricultural economic sectors in Portuguese regions the following model base was used:

$p_{it} = \rho W_{ij} p_{it} + \gamma q_{it} + \varepsilon_{it}$, Verdoorn's equation with spatial effects (5)

where p are the rates of growth of sector productivity across various regions, W is the matrix of distances across regions, q is the rate of growth of output, , γ is Verdoorn's coefficient which measures economies to scale (which it is hoped of values between 0 and1), ρ is the autoregressive spatial coefficient (of the spatial lag component) and ε is the error term (of the spatial error component, with, $\varepsilon = \lambda W \varepsilon + \xi$). The indices i, j and t, represent the regions being studied, the neighbouring regions and the period of time respectively.

The sample for vine and olive crops is referring to 28 regions (NUTs III) of mainland Portugal for the period, in 1999. In practice, we used a relationship similar to the Verdoorn law, but because the available of data, we replaced the productivity by the area and the output by the number of farms. We think these new variables are acceptable proxy, for the Portuguese regions.

5. Data description

The GeoDa programme was used to analyse the data, obtained from the National Statistics Institute, and to carry out the estimations used in this study. GeoDa is a recent computer programme with an interactive environment that combines maps with statistical tables, using dynamic technology related to Windows (Anselin, 2003a). In general terms, functionality can be classified in six categories: 1) Manipulation of spatial data; 2) Transformation of data; 3) Manipulation of maps; 4) Construction of statistical tables; 5) Analysis of spatial autocorrelation; 6) Performing spatial regressions. All instructions for using GeoDa are presented in Anselin (2003b), with some improvements suggested in Anselin (2004).

The analysis sought to identify the existence of variable's relationship by using Scatterplot and spatial autocorrelation, the Moran Scatterplot for global spatial autocorrelation and Lisa Maps for local spatial autocorrelation.

5.1. Analysis of cross-section data

The Scatterplots presented in the annex I allow an analysis of the existence of a correlation between the variable of the model. We see a strong relation for the olive, maybe consequence of this crop occupy farms with big areas. In this way is important to analyse the geographical distribution of vine and olive crops across the Portuguese regions (annex II). We confirm which, than the expected distribution for our country, what we said for the olive is proved by the figures. Mainly, because, this is a crop of the Douro, Beira Interior and the south, locations with big farms.

The Moran Scatterplots which are presented in the annex III concerning the dependent variable, show Moran's I statistical values. The matrix W_{ij} used is the matrix of the distances between the regions up to a maximum limit of 97 Km. This distance appeared to be the most appropriate to the reality of Portuguese NUTs III, given the diverse values of Moran's I obtained after various attempts with different maximum distances. Whatever the case, the choice of the best limiting distance to construct these matrices is always complex. An analysis of the Moran Scatterplots demonstrates that it is in the two crops that a global spatial autocorrelation can be identified.

Below is an analysis of the existence of local spatial autocorrelation with LISA Maps (annex IV), investigated under spatial autocorrelation and its significance locally (by NUTs III). The NUTs III with "high-high" and "low-low" values, correspond to the regions with positive spatial autocorrelation and with statistical significance, or, in other words, these are cluster regions where the high values ("high-high") or low values ("low-low") of two variables (dependent variable and redundant dependent variable) are spatially correlated given the existence of spillover effects. The regions with "high-low" and "low-high" values are "outliers" with negative spatial autocorrelation. Upon analysing the Lisa Cluster Maps to stress the values low-low in the littoral north of the country for the olive and the values high-high in the interior north for the vine, as we expected, have in view the climate and the traditional distribution of this crops across the country.

6. Empirical evidence for Verdoorn's Law, considering the possibility that there are spatial effects

The following presents empirical evidence based on cross-section estimates. These cross- section estimates were carried out with the Least Squares (OLS) and the Maximum Likelihood (ML) methods.

6.1. Cross-section of empirical evidence

This part of the study will examine the procedures of specification by Florax e al. (2003) and will firstly examine through OLS estimates, the relevance of proceeding with estimate models with spatial lag and spatial error components with recourse to LM specification tests.

The results concerning the OLS estimates with spatial specification tests are presented in Table 1. In the columns concerning the test only values of statistical relevance are presented.

Table 1: OLS cross-section estimates with spatial specification tests

Equation: $DIM_i = \alpha + \beta NE_i + \mu_i$

	Con.	Coef.	M'I	LM_l	LMR_l	LM_e	LMR_e	R^2	N.O.
Olive	160.29 (0.05)	2.08* (4.64)	2.12*	3.57*	2.03	2.01	0.48	0.45	28
Vine	-663.88 (-0.34)	0.99* (5.52)	2.42*	0.00	3.37**	2.35	5.72*	0.52	28

Note: M'I, Moran's I statistics for spatial autocorrelation; LM_l, LM test for spatial lag component; LMR_l, robust LM test for spatial lag component; LM_e, LM test for spatial error component; LMR_e, robust LM test for spatial error component;R^2, coefficient of adjusted determination; N.O., number of observations; *, statistically significant for 5%

We confirm what said before, in the data analyses (for the olive) and in the analyses of the spatial autocorrelation (for olive and vine which present strong signals of positive spatial autocorrelation, as we see in the Moran´s I statistical values). In other side, considering the Florax et al. (2003) procedures, we must estimate, only, the vine equations with the component spatial error, because the LM statistical values.

The results for ML estimates with spatial effects for vine are presented in Table 2.

Table 2: Results for ML estimates with spatial effects

Equation: $DIM_i = \rho W_{ij} DIM_i + \gamma NE_i + \varepsilon_i$, com $\varepsilon = \lambda W \varepsilon + \xi$

	Constant	Coefficient	Coefficient$^{(S)}$	R^2	N.Observations
Vine	-1761.73 (-0.72)	1.11* (5.75)	0.38* (1.54)	0.58	28

Note: Coefficient$^{(S)}$, spatial coefficient for the spatial error model; *, statistically significant to 5%; **, statistically significant to 10%.

In this estimation the coefficient value improve, with the consideration of spatial effects, signal of the correct procedures. Mainly, because we extract with this specification what could be a statistical violation.

7. Conclusions

This study has sought to analyse the spatial effects for vine and olive crops across the 28 regions (NUTs III) of mainland Portugal in 1999, with spillover, spatial lag and spatial error effects. To do so, data analysis and cross-section estimates have been carried out with different estimation methods, or, in other words, OLS (least squares method) and non-linear ML (maximum likelihood method). The consideration of these two estimation methods has the objective of following the specification procedures indicated by Florax et al. (2003) who suggest that models are first tested with the OLS method, to test which is the better specification (spatial lag or spatial error) and then the spatial lag or spatial error is estimated with the GMM or ML method.

Considering the "cross-section" data analysis made earlier, it appears that the olive is the permanent agricultural crop with larger areas, reflecting its geographical location. Olives and vines are crops with greater signs of spatial autocorrelation. About the "cross-section" estimations it is confirmed what is said earlier in the data analysis.

As a final conclusion, considering that this two crops are showing strong evidence of positive spatial autocorrelation, that must be taken in count to make interventions in the background (political, technological, etc.) in the sectors of activity associated with them (both upstream and downstream). Especially in olive, since the vine, because of the economic dynamics associated with it, does not need government assistance as directed. The positive spatial autocorrelation clearly indicates that any intervention in a region is necessarily reflected in neighbouring regions. So, this brings unique opportunities to implement technical assistance, as well-based theory of the "oil stain".

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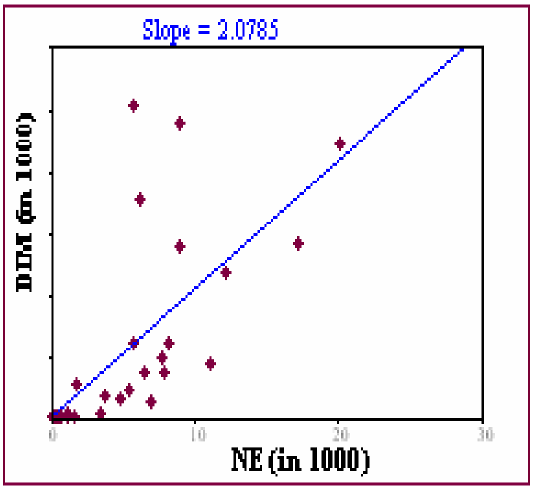
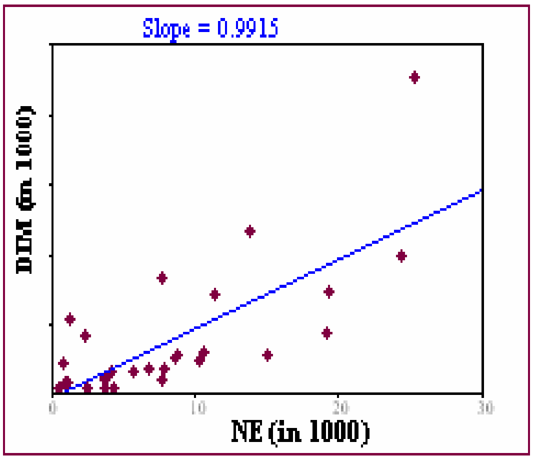
ANNEX I

Figure 1: "Scatterplots" the relationship between area and number of farms for vine and olive

a) Olive



b) Vine



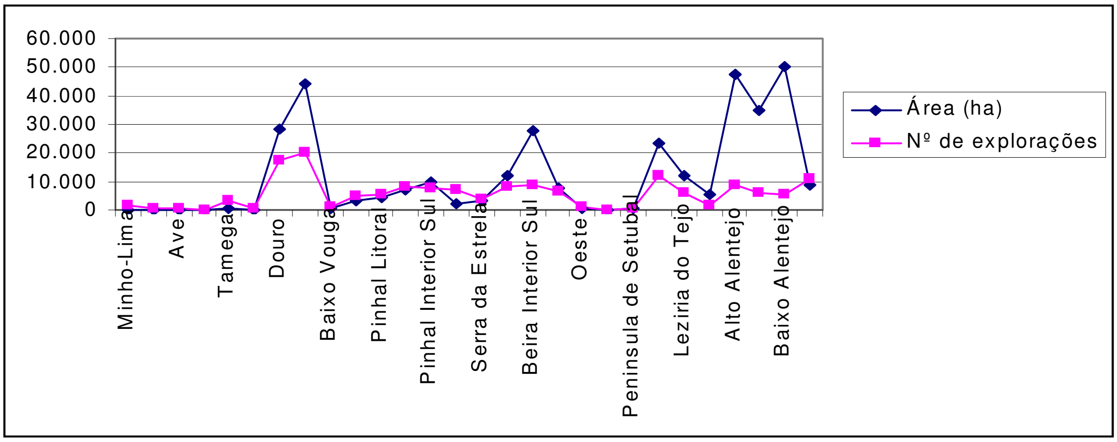
Note: DIM = Area;

NE = Number of farms.

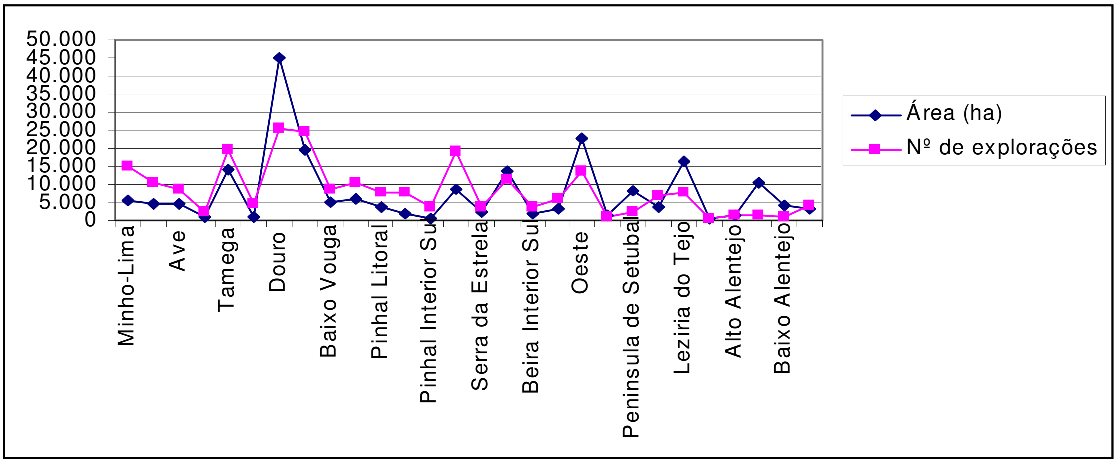
ANNEX II

Figure 2: Distribution of the vine and olive crops between the different NUTS III of Portugal Continental

a) Olive



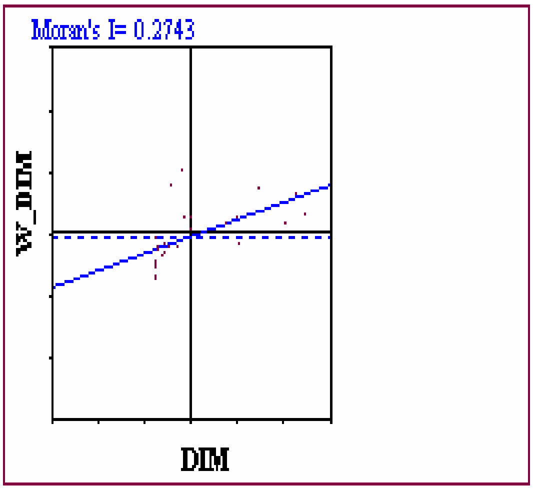
b) Vine



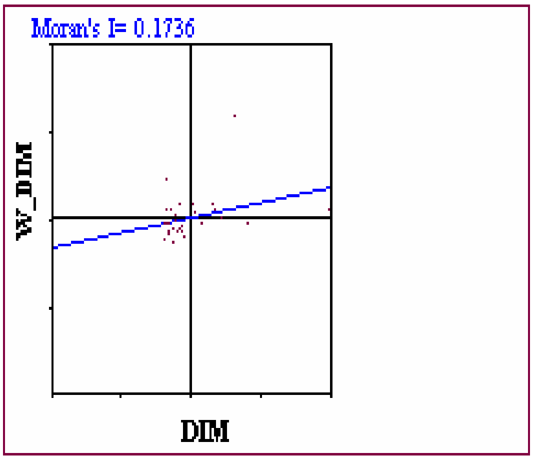
ANNEX III

Figure 3: "Moran Scatterplots" the relationship between area and number of farms for vine and olive crops

a) Olive



b) Vine



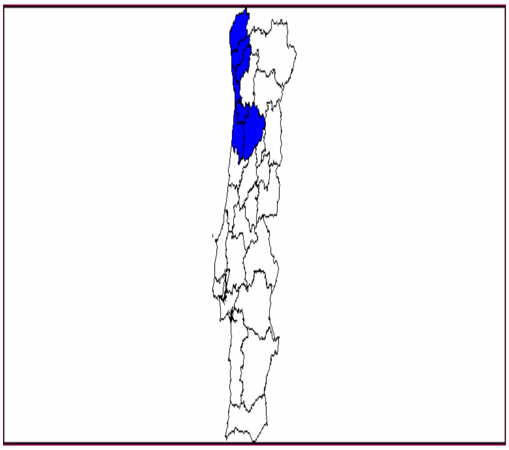
Note: DIM = Area;

NE = Number of farms.

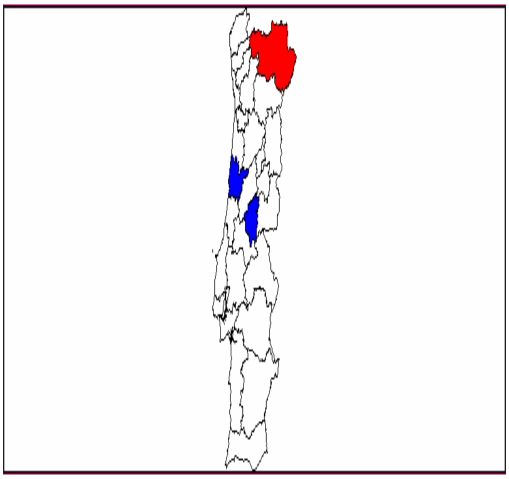
ANNEX IV

Figura 4: "LISA Cluster Map" the relationship between area and number of farms for vine and olive crops

a) Olive



f) Vine



Note: Strong red – values "high-high";

Strong blue – values "low-low";

Weak red - values "high-low";

Weak blue – values "low-high".